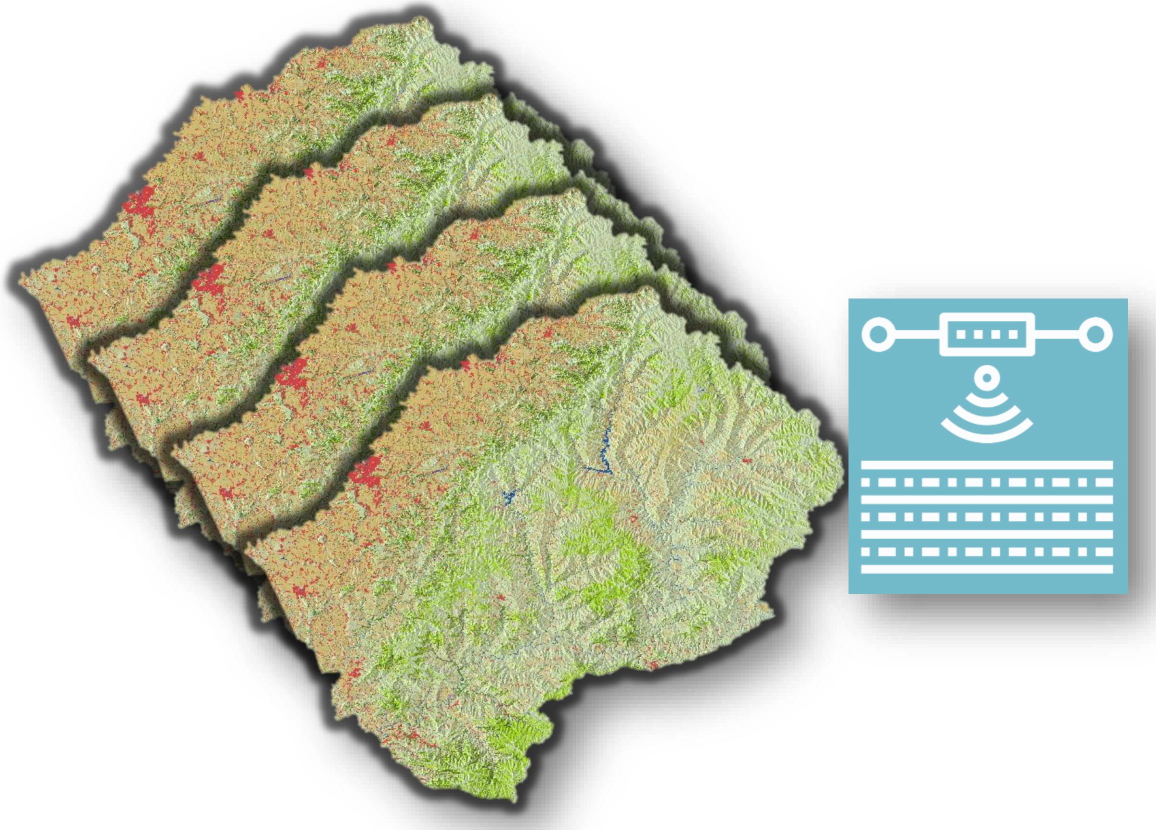


# LESOTHO LAND COVER DATABASE (2017–2021)

## A new methodology for annual land cover production based on Sentinel-2

February 2021 (Lesotho)


**Lorenzo De Simone, FAO**

**William Ouellette, FAO**

# RATIONALE

**Training goal:**

- Bring up to speed local stakeholders with the latest technologies for field data collection, remote sensing data processing and visualization, with the objective of generating more accurate and more frequent land cover data to support sustainable natural resources management and food security
- Reduce the time spent by ministry experts on pre-processing of data and focus on analysing results
- Allow for easier and more user-friendly exploration of land cover data through Google Earth Engine and QGIS

# PROJECT OVERVIEW

**Objectives:**

- Generate an **updated National Land Cover** product for 2017-2021 using a new cost-effective methodology based on Sentinel-2 satellite data, and deliver its components for its annual production in the future
- **Involve the national stakeholders** in its production and its use through participatory approaches and capacity development, to guarantee optimal usability
- **Support with Field Survey Design and Georeferencing best practices** to collect high quality field data

**Impact:**

- Support **accurate reporting and decision-making** for enhancing food security monitoring and natural resources management in Lesotho

# WHY UPDATE LESOTHO'S LCDB?

- Land cover is dynamic and is subject to change over time
- New technologies and free-of-charge satellite data are now available, which were not available back in 2015
- Develop a more automated, cost-effective and reproducible land cover mapping methodology
- Empower local authorities and actors to routinely produce and analyse land cover data for sustainable natural resources management



SOURCE: Earth engine app, 2021. [online]. [Cited 25 February 2022]. https://www.earthengine.app/

# CONTENT OF MODULE II

**Part 1:**

- Refresher on the principles behind the latest **land cover classification methodology**
- Reference **Data Clean-up** and Land Cover **Classification**

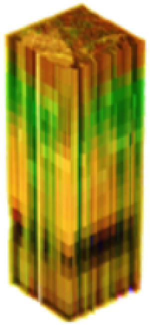
**Part 2:**

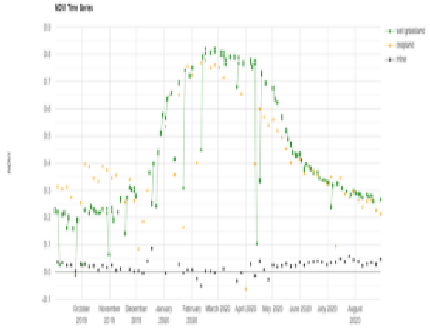
- Land Cover Time Series **Harmonization** and **Post-Processing** in theory
- Land Cover Time Series **Harmonization** and **Post-Processing** in practice

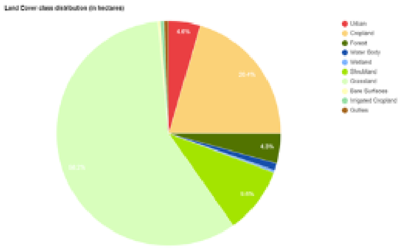
**Part 3:**

- In-depth session on the land cover and land degradation indicators **Dashboard**

# EOSTAT HIGH-LEVEL CONCEPT







**Operational Task Performed**

- Satellite Imagery Preparation
- Reference Data Preparation
- Land Cover Map
- Land Cover Change Statistics

**Skills Acquired**

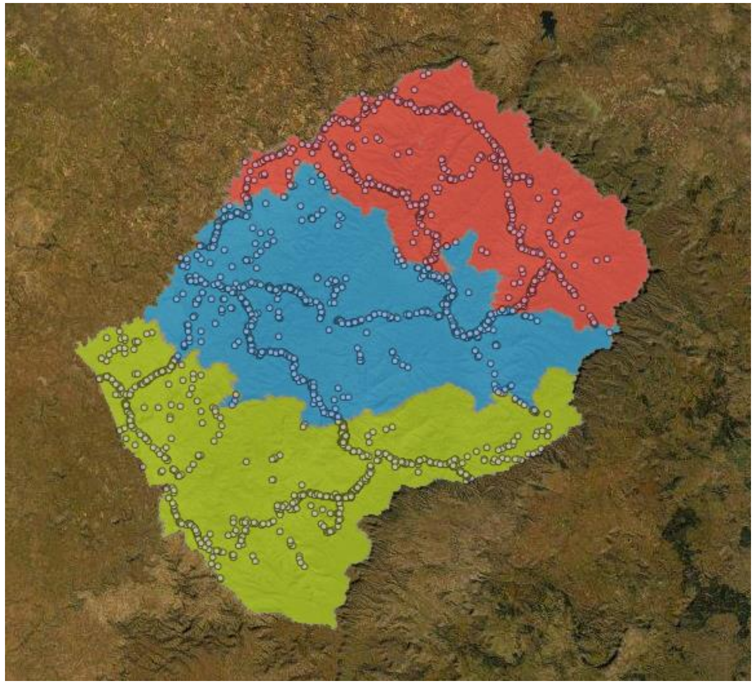
GEE Rookie → Choose, Visualize and Export Data → Clean and Harmonize Reference Data → Create National Land Cover Map → Create Land Cover Statistics & Visualization

**GEE Concepts Covered**

| Satellite Imagery Preparation | Reference Data Preparation | Land Cover Map | Land Cover Change Statistics |
|---|---|---|---|
| ImageCollection, FeatureCollection, Cloud Masking, Temporal Compositing, Add Layers to Map, Export to Drive | List, Array, Reducers, Plot Charts, Interact with land cover reference data on-the-fly using Widgets | Google Colab and GEE Python API, Object-based Image Analysis Built-in Machine Learning Classifiers | Custom algorithm implementation, Statistics from rasters, Raster to vector conversion |

# 2021 LCDB METHODOLOGY

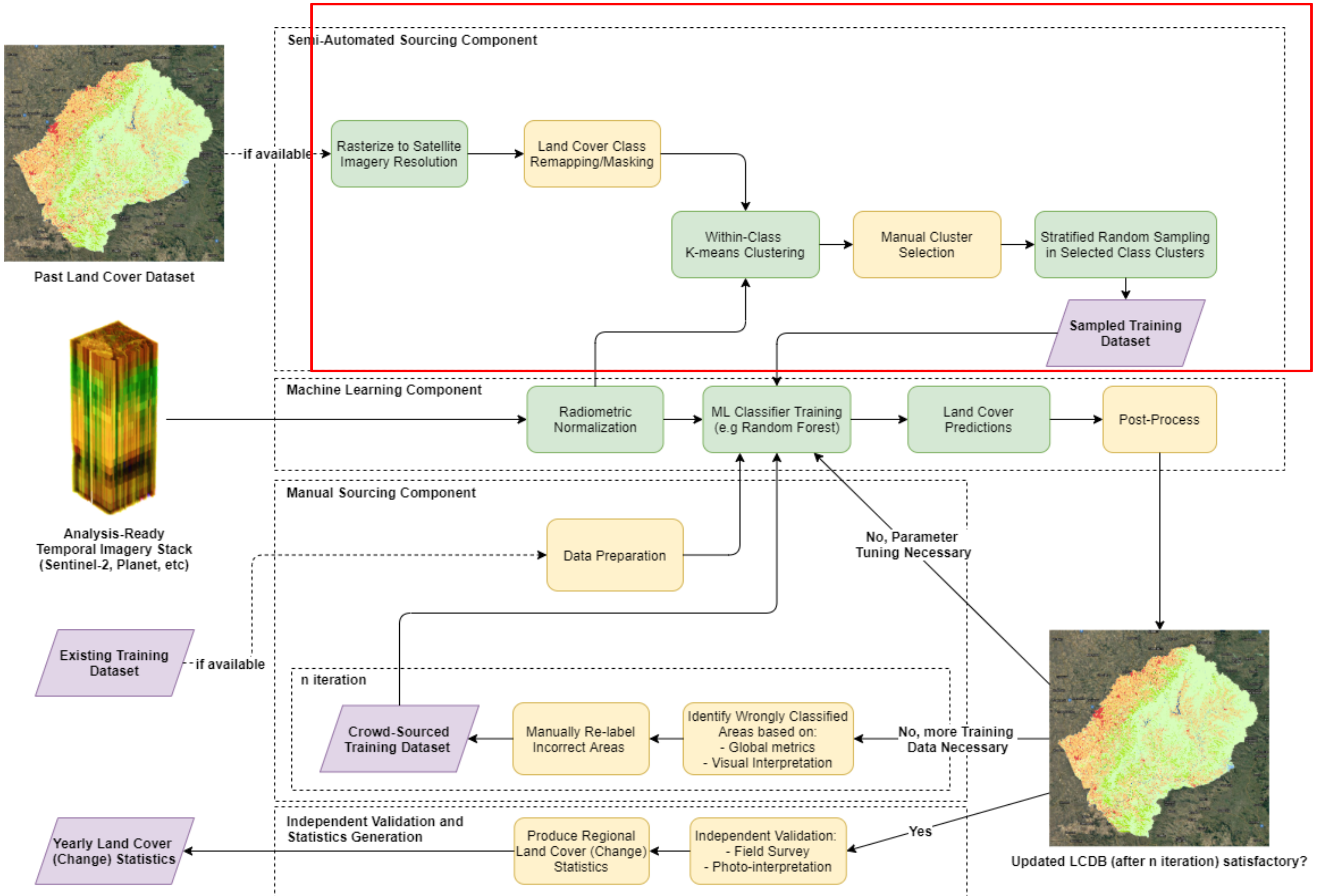
1. **Field campaign 2021** to collect new baseline reference data



2. Train a Machine Learning Model to **"recognize"** landcover types from satellite imagery

3. **Automatically** generate the landcover product

# PROCESSING WORKFLOW



# REFERENCE TRAINING DATA (2021)

Data Sources:

1. 2021 Land Cover Survey carried out by FAO (samples along road network)

   Samples across most classes

2. 2021 Wetland Survey carried out by FAO

   Wetland, Cropland, Grassland, S samples

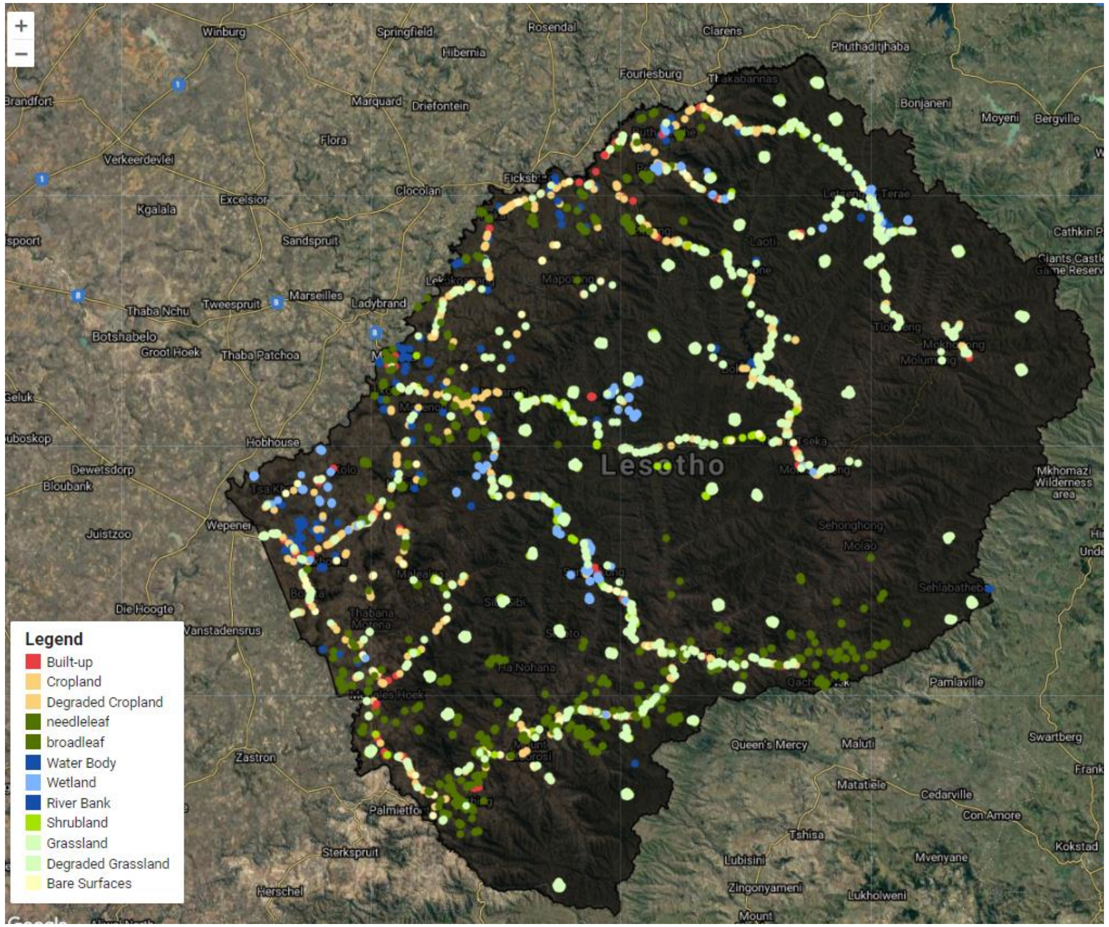
3. LACO-WIKI validation campaign

   Forest samples

4. Land Degradation Surveillance Framework (LDSF) Data

   Shrubland and Grassland samples

***"All models are wrong, but some are useful"***
***George Box***




SOURCE: Earth engine app, 2021. [online].
[Cited 25 February 2022]. https://www.earthengine.app/

# CLEAN-UP TRAINING DATA FOR OTHER YEARS WITH K-MEANS

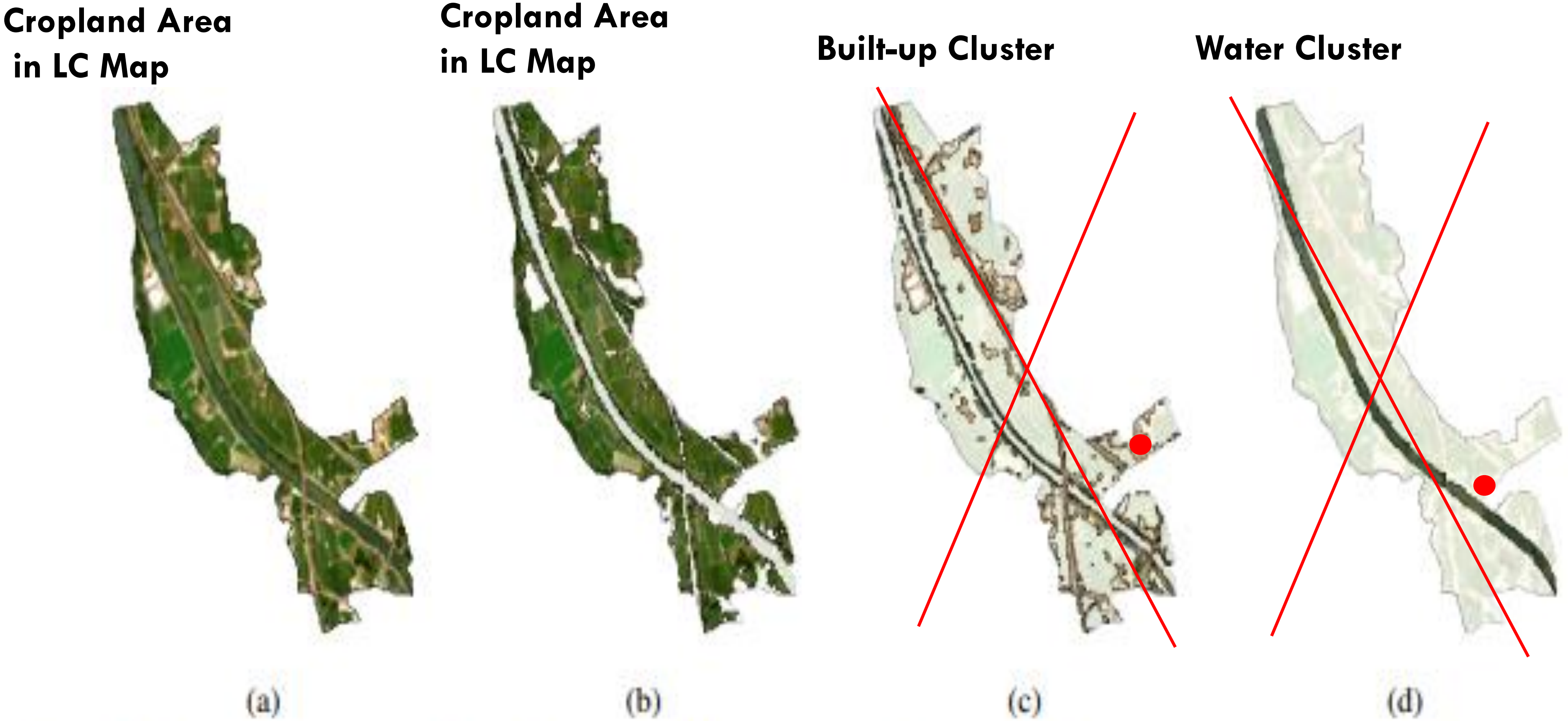
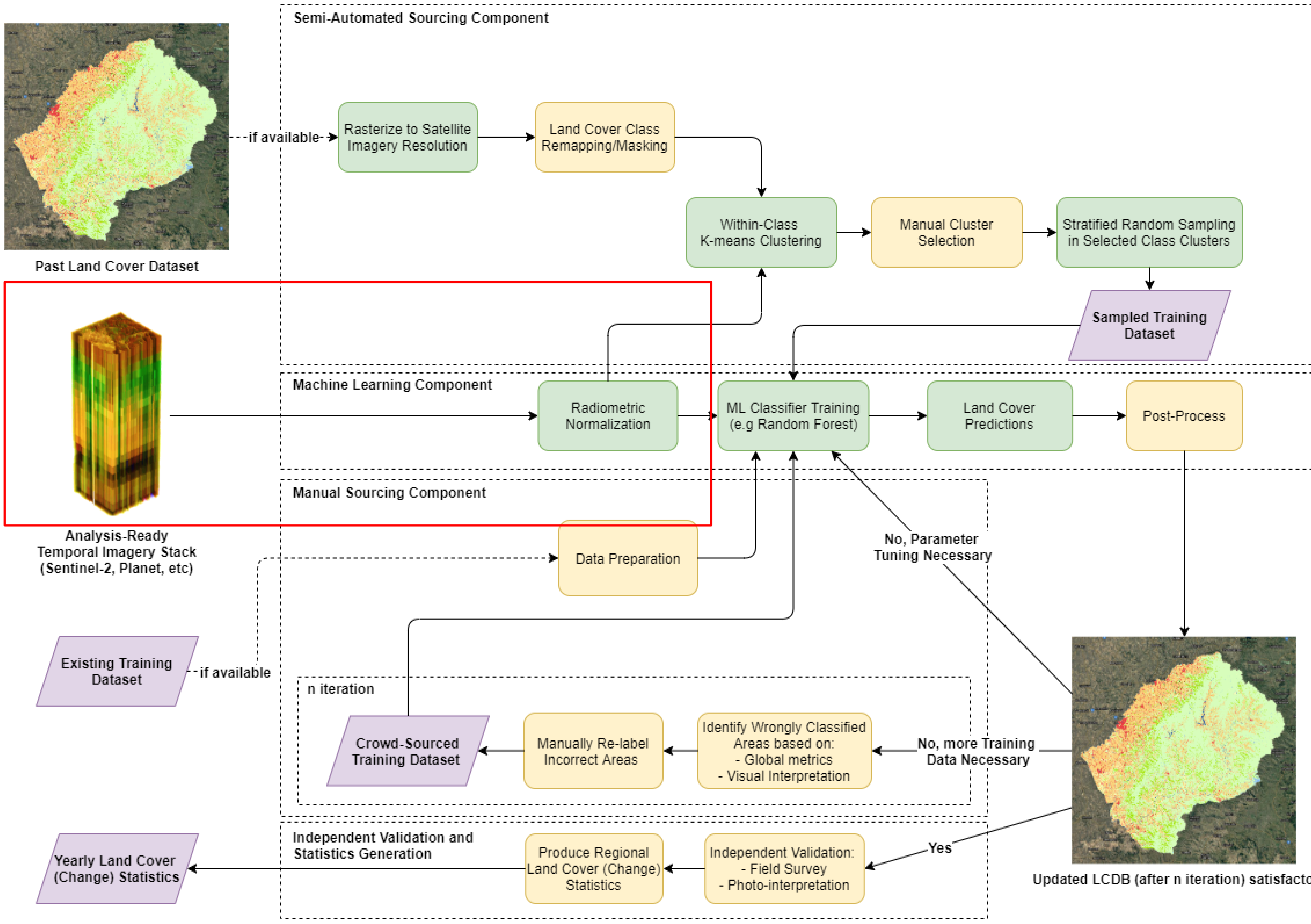
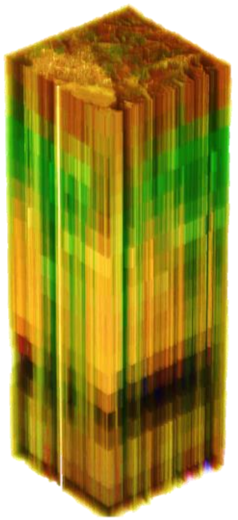



Fig. 2: Qualitative example of polygon $k$-means clustering result: (a) original polygon associated to the "crop" label, (b) dominant land-cover class detected $\mathbf{C}_1$, (c) first minor class detected $\mathbf{C}_2$ (road), and (d) second minor class detected $\mathbf{C}_3$ (river).

# PROCESSING WORKFLOW

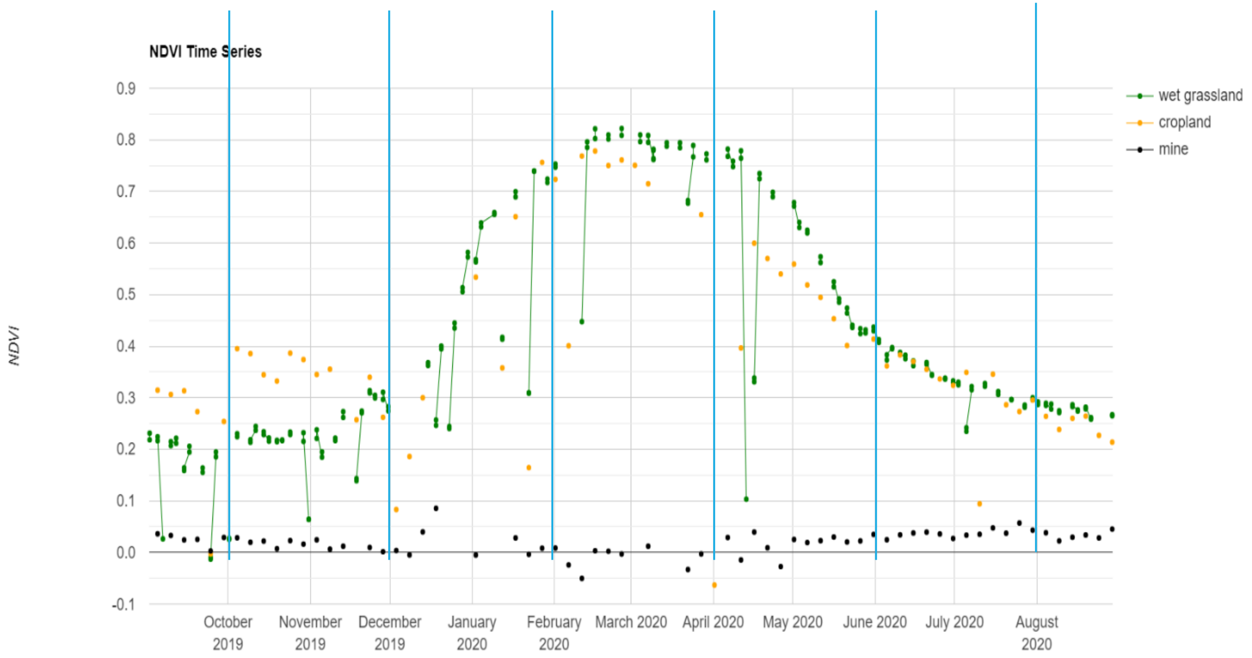


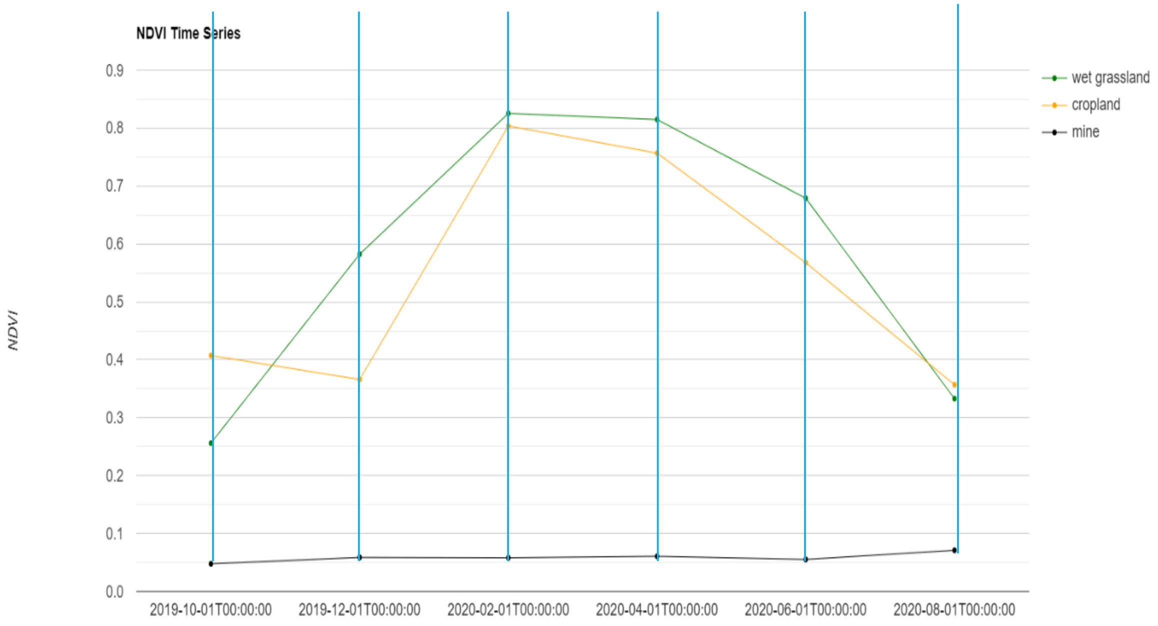
# INPUT FEATURES



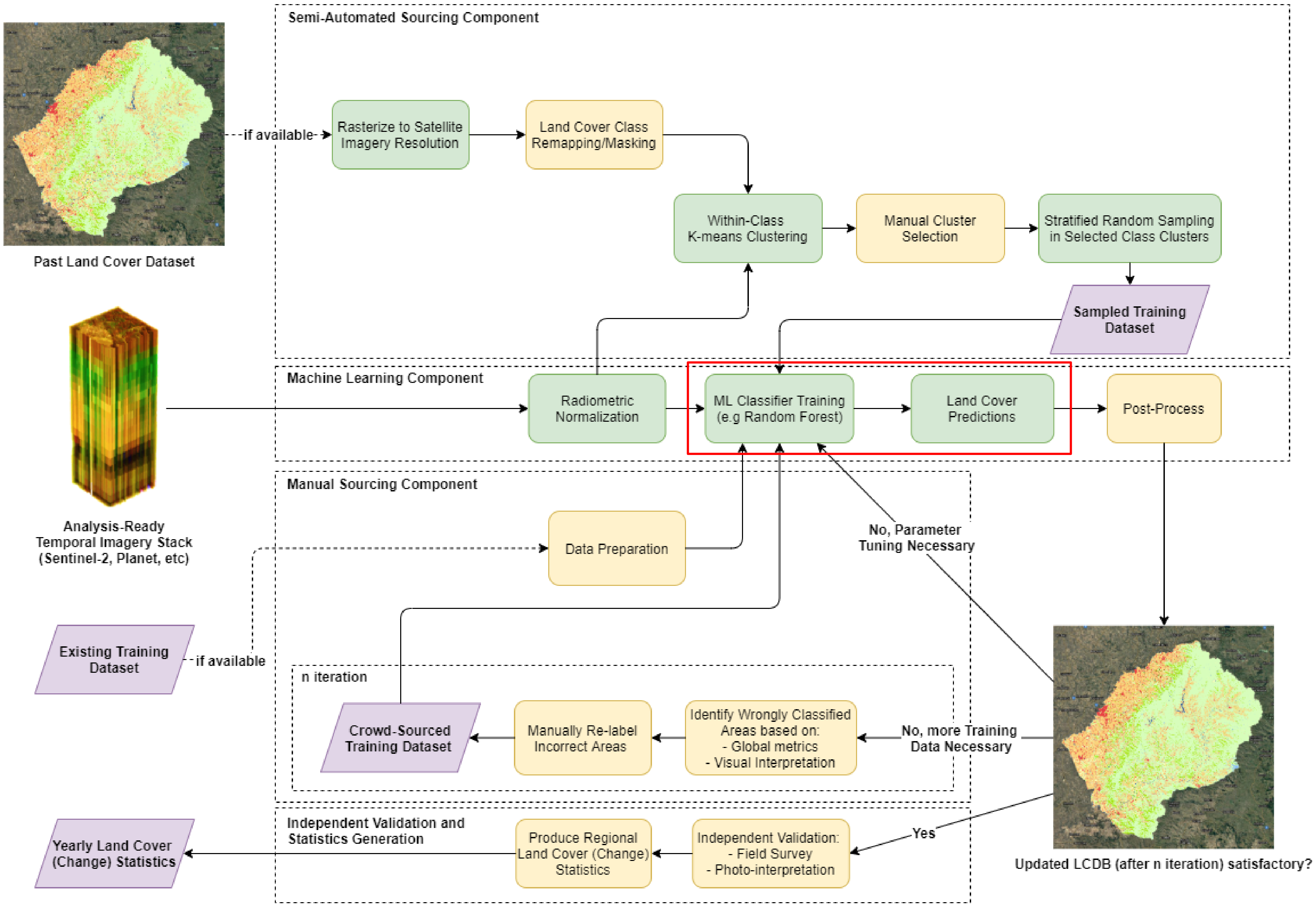
**Input Features Generation: 6 * 2-months, radiometrically normalized, cloud-masked,** Sentinel-2 **Max-NDVI** temporal composites

- All 10 and 20m bands + NDVI + GLCM Correlation and Contrast (image texture) of 10m bands
- **Goals:** reduce data size, keep only cloud-free observations at key phenological stages of the year



# PROCESSING WORKFLOW



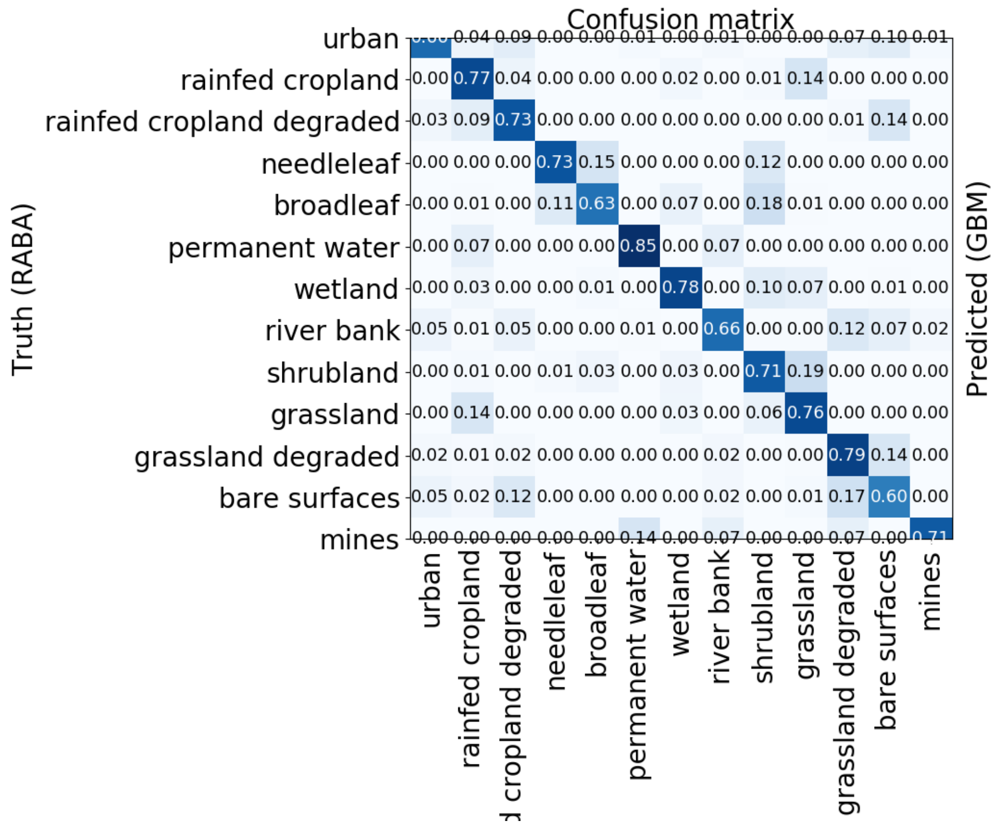
# MACHINE LEARNING MODEL: RANDOM FOREST

**Pixel-based Random Forest Ensemble** Implementation in GEE and validated with:

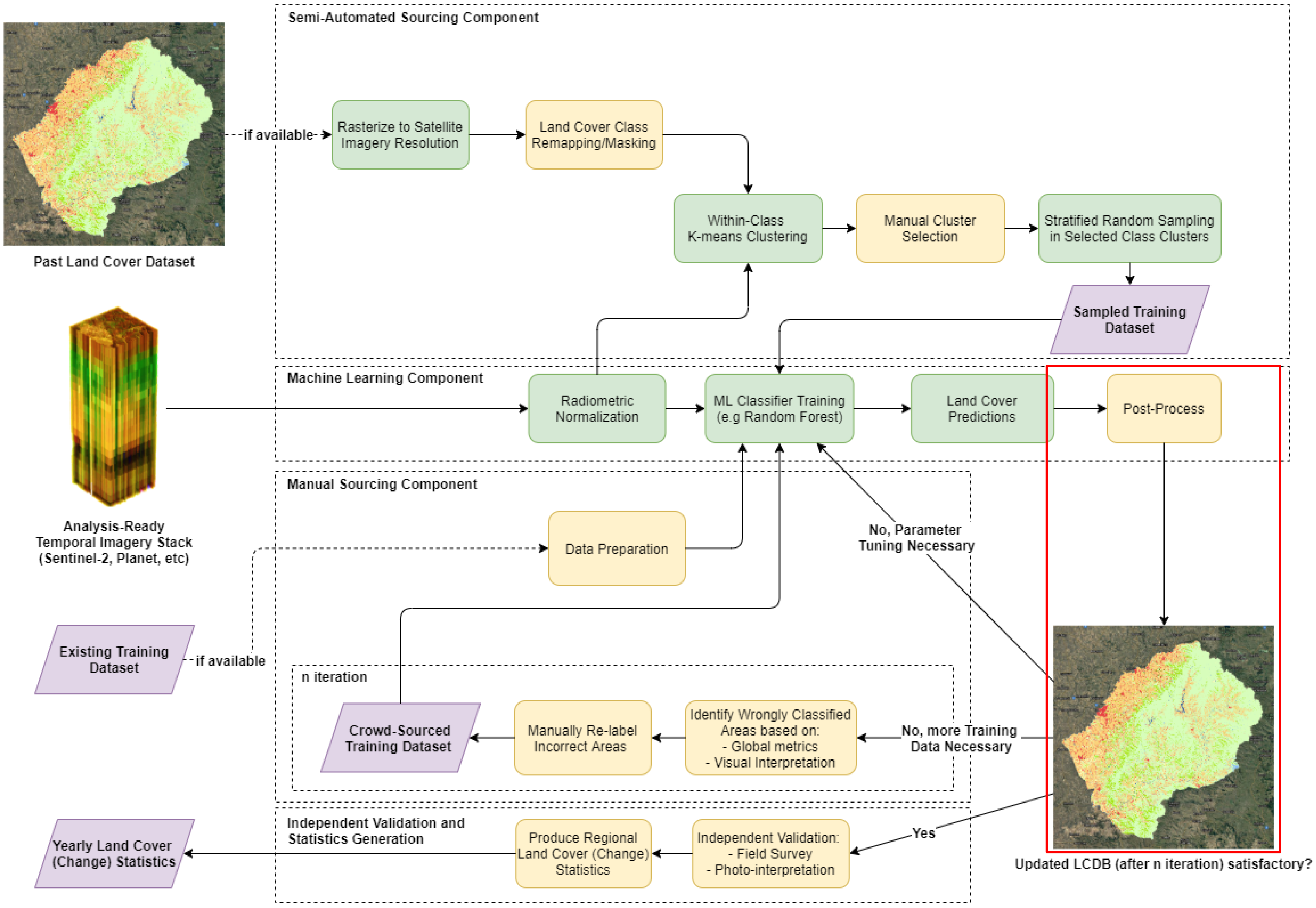
- Confusion matrix
- Visual Assessment

| Land Cover Year | Overall Accuracy (random forest output) | Overall Accuracy (harmonized and post-processed) |
|---|---|---|
| 2017 | 87.34% | 82.66% |
| 2018 | 86.68% | 82.78% |
| 2019 | 86.48% | 84.51% |
| 2020 | 88.54% | 85.19% |
| 2021 | 86.41% | 82.96% |

**Test Results LCDB 2015: Produced Manually and no quantitative validation performed**



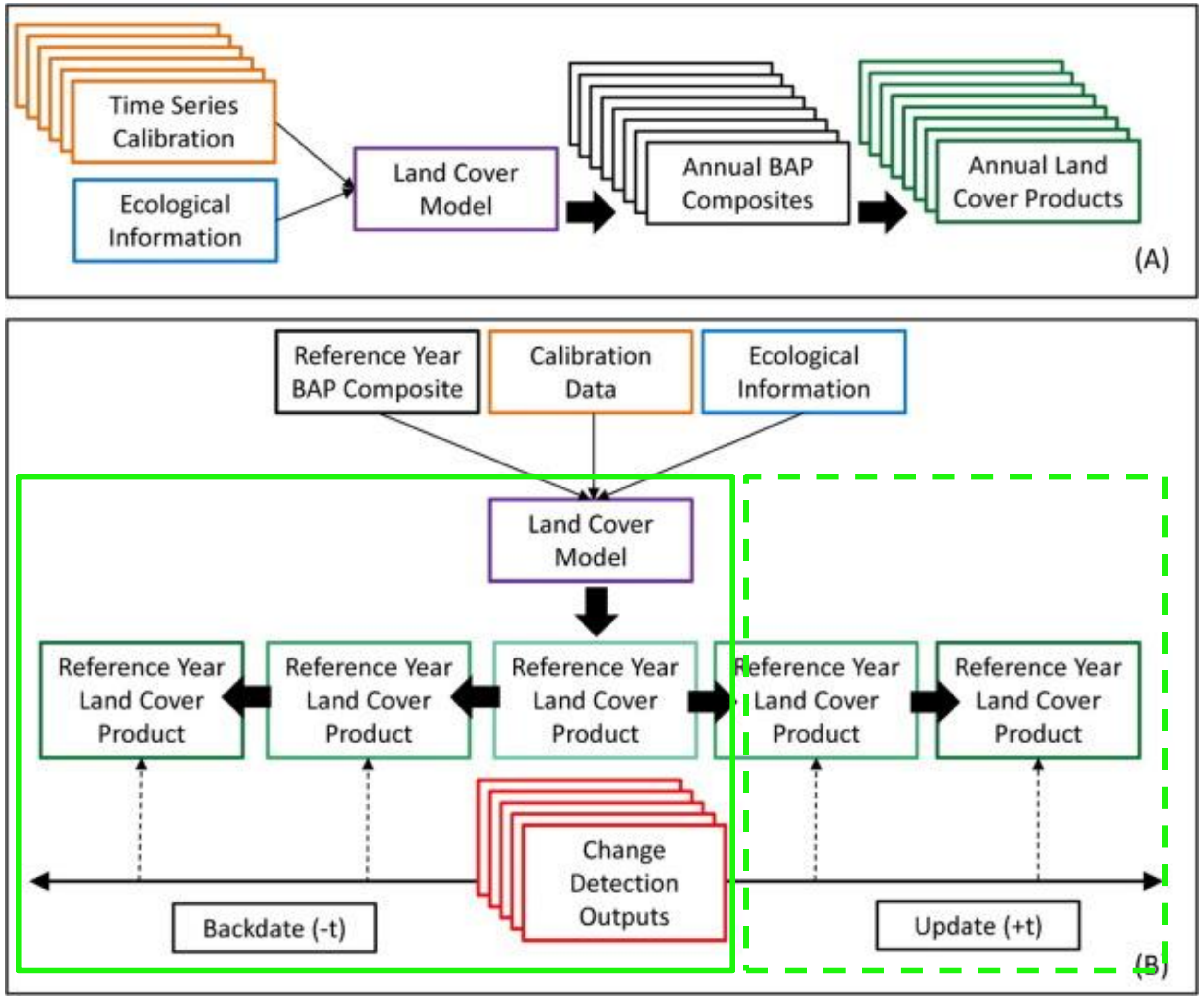
# PROCESSING WORKFLOW



# HARMONIZATION

**Harmonization** implemented across all years (with 2021 as baseline LC data) to:

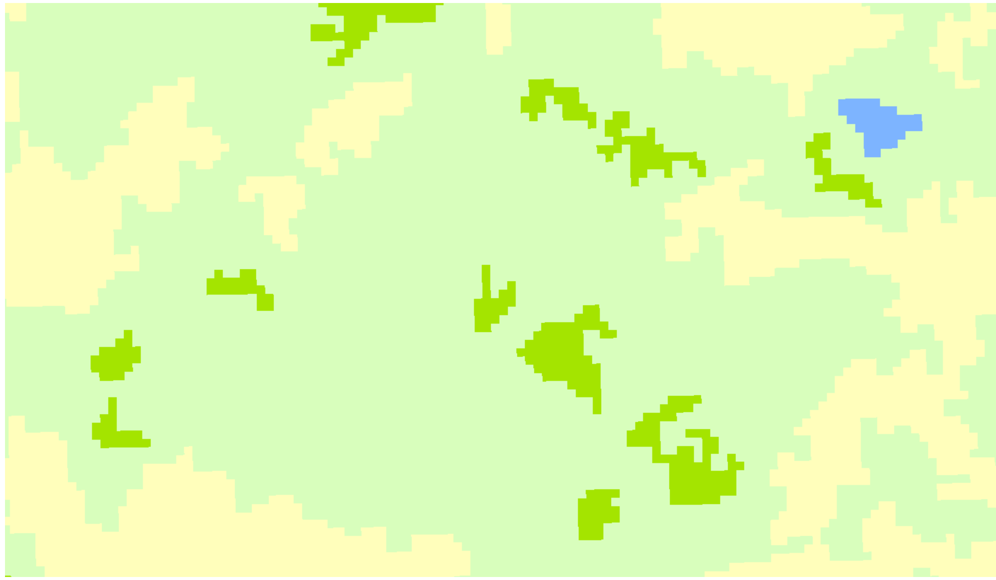
1. Prevent impossible land cover changes (e.g. Grassland to Forest)
2. Prevent inplausible land cover transitions (shrubland → cropland → shrubland in 3 consecutive years)

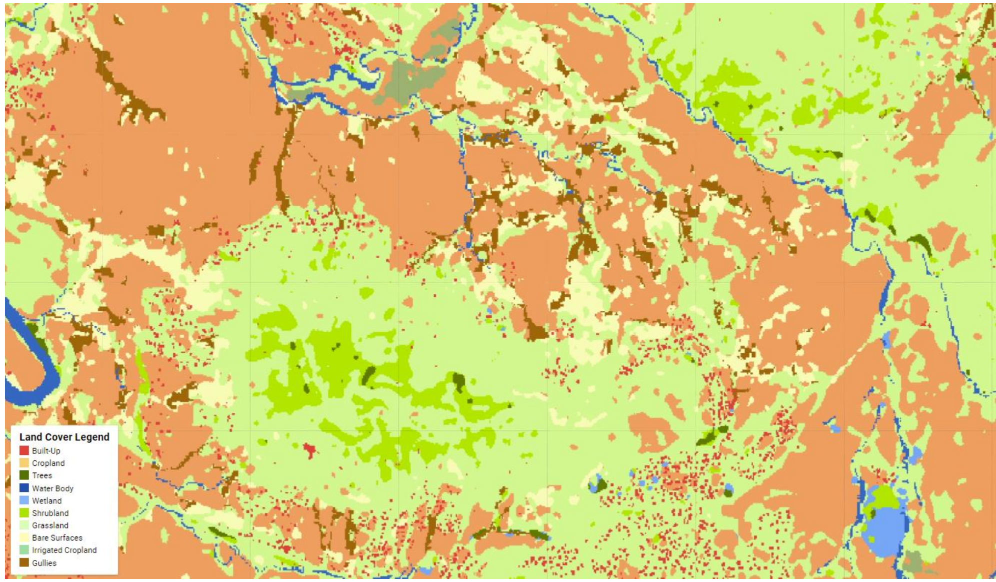


# POST-PROCESSING

**Post-processing rules** implemented mono-temporally (i.e. Independently from other years) to:

1. Improve readability of the product
2. Further correct inplausible/impossible land cover class occurrence
3. Introduce new land cover classes that were not suited for classification alongside other classes (gullies and irrigated cropland)





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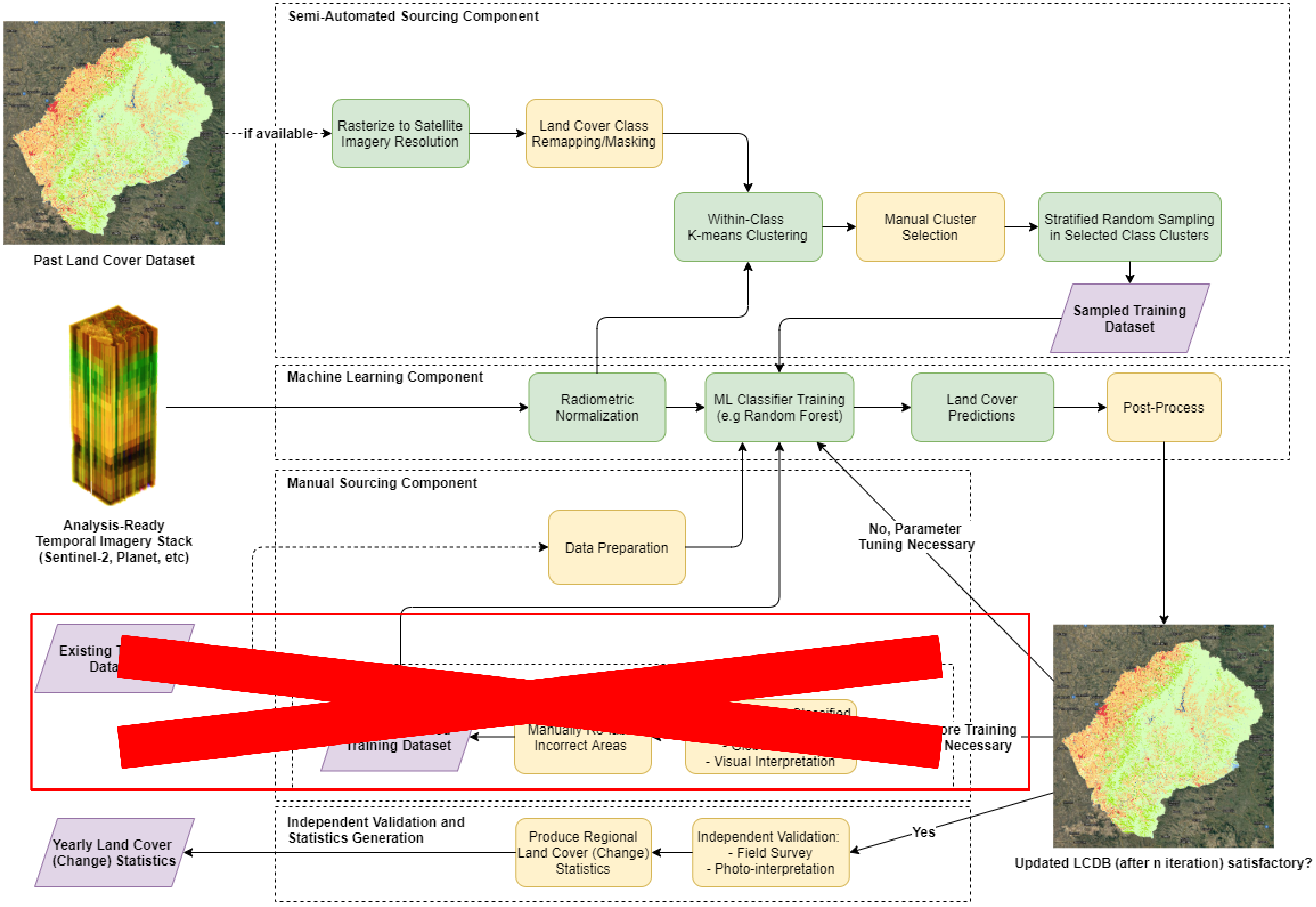

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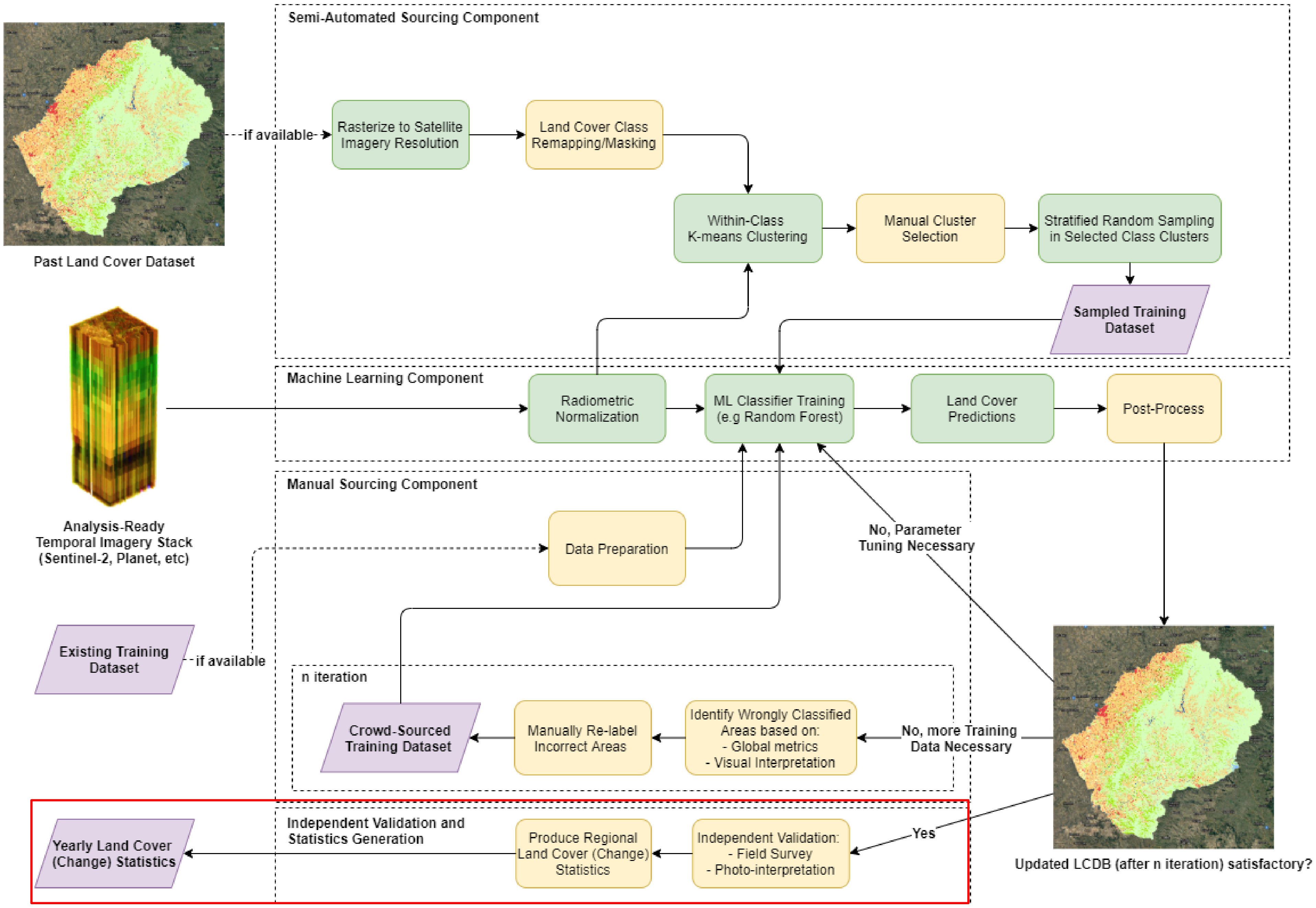
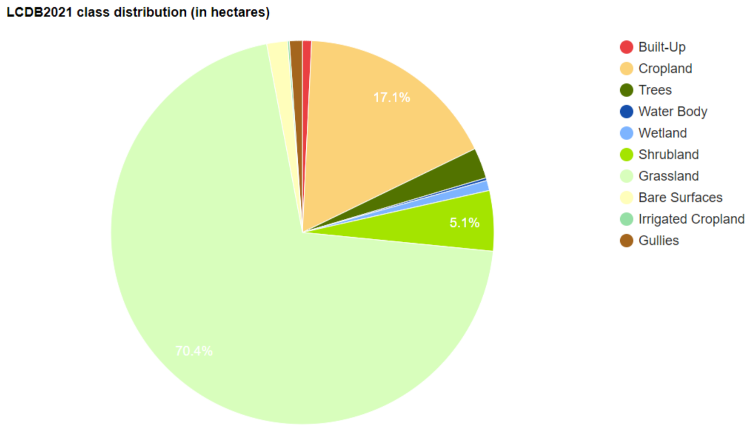
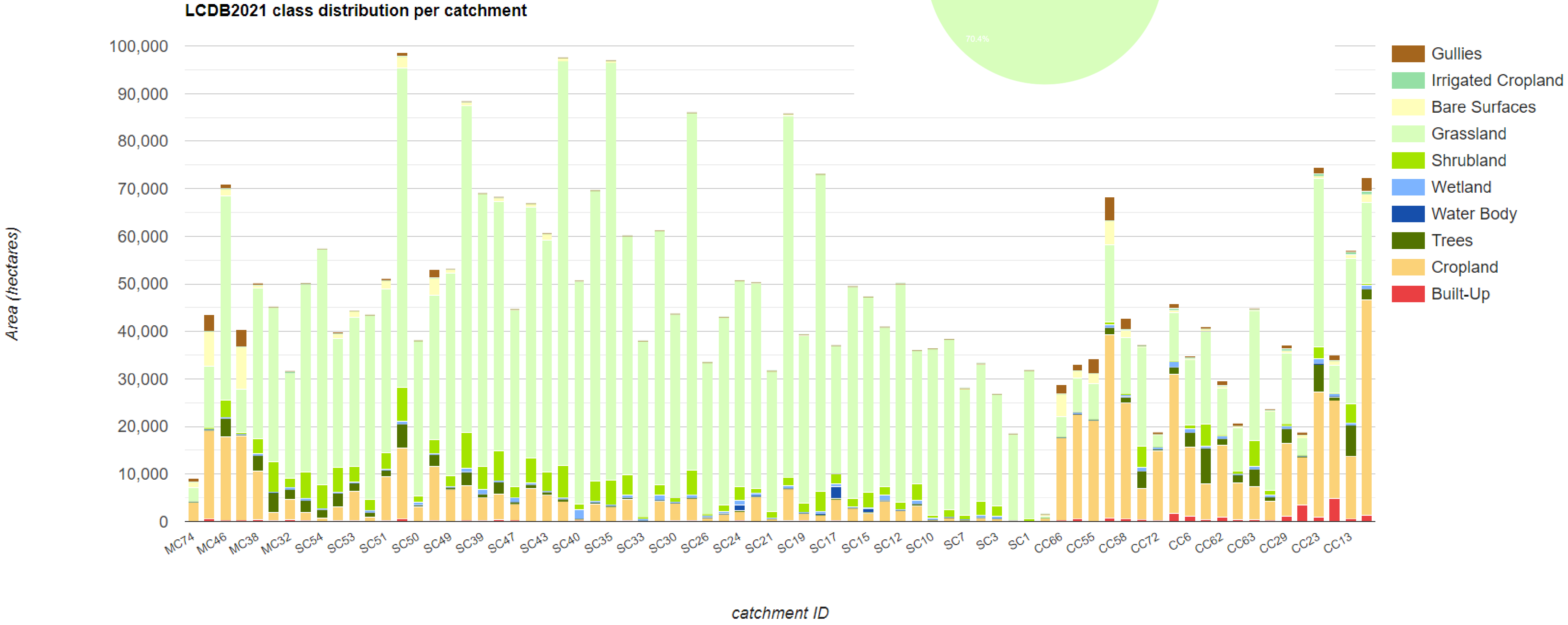


# GLOBAL LAND COVER STATISTICS



# MAPS DISCLAIMER

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# REFERENCES


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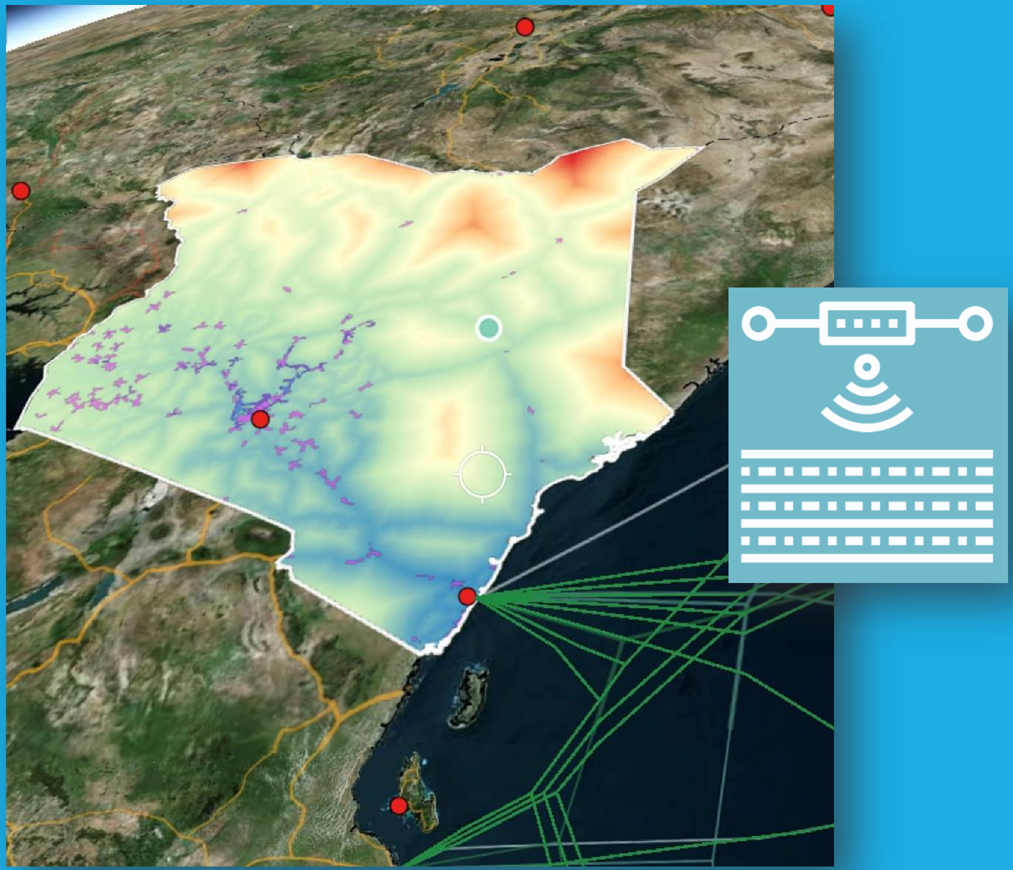

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